Gender and the Automobile

Analysis of Nonwork Service Trips

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With a focus on individual motorists in car-owning households in Germany, this analysis econometrically investigates the determinants of automobile travel for nonwork service activities against the backdrop of two questions: (*a*) Does gender play a role in determining the probability of car use and the distance driven? and (*b*) If so, how is this role mitigated or exacerbated by other socioeconomic attributes of the individual and the household in which he or she resides? Drawing on a panel of data collected between 1996 and 2003, Heckman's sample selection model is specified to control for biases that otherwise could arise from the existence of unobservable variables that determine both the discrete and the continuous choices pertaining to car use. The results indicate that although women, on average, undertake more nonwork travel than men, they undertake less such travel by car, implying a greater reliance on other modes. Moreover, employment status, age, the number of children, automobile availability, and the proximity to public transit are all found to have significantly different effects on the probability of nonwork car travel between men and women but—with the exception of automobile availability—not on the distance driven. Taken together, these results suggest that policies targeted at reducing automobile dependency and associated negative externalities, such as congestion, are unlikely to have uniform effects across the sexes. These findings have implications for both policy evaluation and travel demand forecasting.

Understanding gender-based differences in mobility has emerged as an important priority in transportation policy. There are several dimensions along which the behavior of female travelers has been found to diverge from that of male travelers. Among the most widely documented differences are that women commute shorter distances, engage in more nonwork travel, have a stronger tendency to link trips, and are more likely to respond to changing travel circumstances than men. Despite widespread consensus on the prevalence of these behavioral patterns, one important area still muddled by inconclusive and sometimes contradictory results concerns automobile travel. Whether, why, and to what extent gender disparities in driving exist is an especially pressing issue, given the significance of this travel mode to a range of social welfare issues. This significance extends beyond concerns relating to pollution, congestion, and other externalities associated with automobile use to include issues of access and equity. With more women entering the labor force while simultaneously bearing a disproportionate share of the responsibility for household tasks, the question of whether and how transportation policy should be designed to take into account gender differences in automobile use assumes increasing relevance.

An important step in systematically assessing these issues is to identify the socioeconomic and geophysical factors that determine the incidence and extent of automobile use among individual household members. Gender differences should figure into such assessments, inasmuch as these differences can complicate attempts to anticipate the effects of transportation demand management policies. If, for example, the objective is to design interventions that encourage the substitution of public transit for automobile travel, then quantification of the propensity of men and women to switch travel options—to the extent that these propensities differ—would be necessary for gauging both overall impacts and distributional effects. Likewise, a comprehensive assessment of carpooling programs or staggered work hours may well require an analytical framework distinguishing between male and female driving behavior, particularly if the differences in driving behavior are a function of factors directly affected by the intervention, such as employment status. In general, the question of whether gender differences in car travel warrant greater scrutiny is relevant to a range of transportation policy issues but is a question on which there is a dearth of conclusive research.

The present paper aims to fill this void by estimating an econometric model of car use with a panel of travel diary data collected in a nationwide survey of German households. Germany provides a particularly interesting case study because of several trends pointing to an increased share of women in the pool of automobile drivers, including higher labor force participation rates among women and a growing proportion of women in possession of a driver's license. Although similar developments have been documented in the United States, the United Kingdom, and other Western countries, their implications for automobile access and the distances traveled by the two sexes remain unclear.

Several studies from the United States have suggested that, although women tend to have more complicated activity patterns and make more serve-passenger trips than men, they have unequal access to the car and conduct more of their travel by public transportation or by foot than men (*1–7*). Dissenting from these findings, Gordon et al. (*8*) and Rosenbloom (*9*) find little difference between men and women in private automobile use, based on analyses of the 1983 Nationwide Personal Transportation Survey and 1990 Public Use Micro Sample, respectively. Mixed evidence also has surfaced in the United Kingdom. One recent study notes that despite a strong growth in the rate of driver's license holding among women, men undertake, on average, 15% more car trips as the driver than women (*10*), whereas another study finds no significant effect of gender on the likelihood of using the car as a commute mode (*11*). In one of the few studies conducted on this issue in the German context, Heine et al. find that children

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are the most important factor in increasing the rate of car use by women, which they attribute to the traditional role of women in assuming shopping and accompaniment duties, as well as to the security aspects of caring for children in the case of emergencies (*7*). A more recent study by Vance et al. also finds that the presence of children in German households equalizes the likelihood of car use between men and women (*12*).

This paper builds on the body of literature described above in several respects. First, the issue of gender and automobile access is approached from two angles: the discrete choice of whether to drive and the continuous choice of the distance traveled. To the extent that these two decisions are related and, moreover, influenced by factors unobservable to the researcher, Heckman's sample selection model was chosen as the appropriate technique for addressing biases that could otherwise emerge from sample selectivity. Second, beyond testing the effect of gender, interaction terms are included to explore whether this effect is modified by other socioeconomic attributes describing the individual and the household in which he or she resides. The specific interest is in testing for the differential effects of gender by age, employment status, the presence of children, the availability of an automobile, and the proximity of public transport, five factors that are frequently cited as accounting for variations in the share of female drivers. Third, assessment of these factors moves beyond the standard focus on the significance and magnitude of the parameter estimates to consider their implications for predicted outcomes. To this end, a Monte Carlo simulation technique proposed by King et al. (*13*) was implemented to explore the predictions of the model and, more importantly, the associated degrees of uncertainty. Finally, unlike much of the work on automobile use to date, the focus here is specifically on nonwork travel that encompasses shopping and delivery-related tasks, as such travel is indicative of gender differences in household maintenance responsibilities.

The remainder of the paper is organized as follows. The next section describes the data, including the measurement of the dependent variable and relevant descriptive statistics to aid with the interpretation of the model results. Section three describes the model specification. Section four catalogues the results, and section five provides conclusions.

DATA

The data used in this research are drawn from the German Mobility Panel (MOP), a multiyear travel survey financed by the German Federal Ministry of Transport, Building, and Housing (*14*). The survey, which is ongoing, was initiated in 1994. In its initial years from 1994 to 1998, MOP focused exclusively on the former West German states, but in 1999 its scope was broadened to include the new federal states.

The panel is organized in waves, each comprising a group of households surveyed for a period of 1 week over each of 3 years. The data used in this paper are from eight waves of the panel, spanning from 1996 to 2003. The analysis focuses exclusively on those households that owned at least one car, roughly 85% of the sample. The analysis is further limited to household members who are at least 18 years old and who possess a driver's license (the minimum age for possession of a license in Germany is 18 years). Finally, as one of the explanatory variables of interest in the study is employment status, data for weekends were excluded from the sample. Overall, 44,842 individual person-days of observations are included in the sample with which the model is estimated. To correct for the nonindependence of repeat observations, the model is specified by using robust regression techniques that account for clustering on the individual. The measures of statistical significance presented are thus robust to the appearance of individuals over multiple time points in the data.

Households that participate in the survey are requested to fill out a questionnaire eliciting general household information and person-related characteristics, including gender, age, and employment status. In addition, all household members over 10 years of age fill out a trip log that captures relevant aspects of everyday travel behavior, including the distances traveled, the modes used, the activities undertaken, and activity durations. To construct the dependent variable, data from the trip logs were used to derive a measure of the total distance driven by the individual over the course of a day for nonwork activities that involve shopping or the delivery of people and items at the destination.

Table 1 presents descriptive statistics that provide some insight into how such activities break down by mode and gender. Consistent with expectations, women undertake roughly 14% more nonwork travel in total, averaging 6.5 km/day, compared with 5.5 km/day for men. With respect to nonwork travel by modes other than the car (which includes public transit and nonmotorized transport), the differences between the sexes are somewhat more pronounced, with women averaging 2.2 km/day, roughly 1.4 km/day, or 61%, more than that of men. However, these roles are reversed when nonwork travel by use of the car, the focus of the subsequent modeling, is examined. For this category, men register a slightly higher figure of 4.7 km/day, compared with 4.3 km/day for women.

TABLE 1 Nonwork Travel (kilometers per day) by Gender and Mode

	Mean	SD	% of Total Travel	*n*	Difference in Means	*t*-Test
Total nonwork travel						
Female	6.450	12.809		21,504	0.904	7.461
Male	5.546	12.835		23,338		
Total nonwork travel by car						
Female	4.279	9.781	66.3	21,504	−0.435	−4.291
Male	4.714	11.658	85.0	23,338		
Total nonwork travel by other modes						
Female	2.171	8.736	33.7	21,504	1.339	19.227
Male	0.832	5.510	15.0	23,338		

MODELING APPROACH

Estimator

Roughly 29% of the individuals in the data set who possess a driver's license and who live in a car-owning household do not use the car for nonwork travel purposes on a given day. Given the interest in simultaneously modeling the determinants of car use and the distance traveled, this feature of the data suggests the specification of Heckman's sample selection model (*15*). A key advantage of the model is that it controls for sample selection biases that could otherwise arise from the existence of unobservable variables that determine both the discrete and the continuous choices pertaining to car use. Such biases may emerge from the possibility that the determinants of car use are not random: those individuals who would travel short distances are the same individuals who are less likely to use the car. To the extent that such individuals are not included among the subsample of observations used in the estimation of a model of distance traveled, the expected value in this subsample will be biased upward.

The Heckman model considers that observations are ordered into two regimes. In the context of the present example, these regimes are defined by whether the individual uses a car for nonwork travel. The first stage, referred to as the selector equation, defines a dichotomous variable indicating the regime into which the observation falls:

$$S_i^* = \tau' Z_i + u_i \tag{1}$$

$$S_i = 1 \qquad \text{if } S_i^* > 0$$

and

$$S = 0 \qquad \text{if } S_i^* \leq 0 \tag{2}$$

where

- S_i^* = latent variable indicating the utility from car use for individual *i,*
- S_i = indicator for car use status,
- Z_i = determinants of this status,
- τ' = vector of associated parameter estimates, and
- u_i = error term with a standard normal distribution.

After the estimation of τ by the probit maximum-likelihood method, the second stage involves estimation of an ordinary-least-squares regression of distance traveled, conditional on the set of all individuals who use the car (S) equal to 1. To control for sample selectivity, this second-stage regression appends the inverse Mills ratio (IMR) calculated from the linear predictions of the probit model as an additional explanatory variable. This second-stage regression is referred to as the outcome equation and is written as

$$E\left(y_i \mid S_i = 1, x_i\right) = \beta' x_i + \beta_\lambda \lambda_i \tag{3}$$

where

- y_i = dependent variable, measured here as the kilometers of daily nonwork vehicle travel;
- x_i = explanatory variables;
- β = associated parameters to be estimated; and
- λ_i = IMR, defined by the ratio of the density function of the standard normal distribution, ϕ, to its cumulative density function, Φ. If it is significant, the estimate on this term indicates that sample selectivity is present.

Interpretation of Marginal Effects

Several complications arise in interpreting the coefficient estimates from the Heckman model. With respect to the probit selector equation, interest generally focuses on the effects of changes in one of the independent variables *k* on the probability of an outcome of 0 or 1, as given by the following formula (*16*):

$$\frac{\partial \Phi\left(\tau' Z_i\right)}{\partial Z_{ik}} = \phi(\tau' Z) Z_k \tag{4}$$

These effects, which are generally calculated at the mean of the other independent variables, can be requested in the output of most statistical software packages, although some care must be taken in their interpretation when interaction terms are involved. As Ai and Norton discuss (*17*), the interaction effect for two variables in nonlinear models such as the probit model requires computation of the cross-derivative

$$\frac{\partial^2 \Phi(\tau' Z_i)}{\partial Z_{i1} \partial Z_{i2}}$$

whereas, standard computer software typically displays the effect equal to

$$\frac{\partial \Phi(\tau' Z_i)}{\partial (Z_{i1} Z_{i2})}$$

They show that the latter calculation often results in false inferences with respect to both the sign and the significance of the interaction term. Consequently, their recommendation to calculate the interaction effect as given by the cross-derivative is followed.

As with the selector coefficients, care is also required in interpreting the coefficients from the outcome equation, particularly when the variable additionally appears in the selector equation. In this case, the marginal effect is given by (*18*)

$$\frac{\partial E\left(y \mid S > 0, x\right)}{\partial X_k} = \beta_k - \tau_k \beta_\lambda \lambda\left(\lambda + \tau' Z\right) \tag{5}$$

where the term after the minus sign corrects for the selectivity effect. To handle the case of dummy variables that appear in both equations, the formula suggested by Hoffmann and Kassouf (*19*) is adapted and is expressed as

$$\frac{\partial E\left(y \mid S > 0, x\right)}{\partial X_k} = \beta_k - \beta_\lambda \left(\lambda_1 - \lambda_0\right) \tag{6}$$

where IMR takes on two values corresponding to the dummy variable equal to 1 (λ_1) and 0 (λ_0), respectively. The statistical significance of the parameters estimated from Equations 5 and 6 is calculated by the Delta method, which uses a first-order Taylor expansion to create a linear approximation of a nonlinear function, after which the variance and measures of statistical significance can be computed.

To further facilitate the interpretation of select results from the model, the predicted outcomes and associated 95% confidence intervals for particular variables of interest are plotted by using a statistical simulation method described by King et al. (*13*). Recognizing that the parameter estimates from a maximum-likelihood model are asymptotically normal, the method uses a sampling procedure akin to Monte Carlo simulation in which a large number of values—say, 1,000—of each estimated parameter are drawn from a multivariate normal distribution. Taking the vector of coefficient estimates from the model as the mean of the distribution and the variance–covariance matrix as the variance, the simulated parameter estimates can be used to generate predicted values and, more importantly, the associated degree of uncertainty. As illustrated below, the generation of confidence intervals, in particular, reveals insights that would otherwise be neglected were the analyst to focus exclusively on the parameter estimates and their standard errors. The annotated code for the generation of these and all other results presented in the paper, which was written by using Stata software, is available from the authors on request.

Explanatory Variables

A well-known impediment in implementing the Heckman model emerges when there is a high degree of multicollinearity between the independent variables and IMR, which results in high standard errors on the coefficient estimates and parameter instability. Effectively addressing this problem and controlling for sample selectivity bias in the second stage regression require the selection of at least one variable that uniquely determines the discrete choice of car use but not the continuous choice of distance traveled. In the present example, the selection of such identifying variables can be informed by consideration of the fixed costs of car use (i.e., costs that are incurred or avoided with access to the car but not with distance traveled). Three identifying variables that capture the attributes of the neighborhood in which the individual resides are included: the distance to the nearest public transport stop (minutes), a dummy variable indicating whether that stop services rail transport as opposed to bus (railtransit), and a dummy variable indicating access to a private driveway at the individual's residence (prvtpark). The first of these, which is additionally included as an interaction term with a female dummy variable, captures the fixed costs associated with the cost of access to alternative modes and is expected to have a positive effect on the likelihood of car use. The rail dummy variable is expected to have a negative effect, as its service attributes (e.g., speed and comfort) are generally superior to those of bus transport. Finally, the private driveway dummy variable is expected to have a positive effect, since the lower search costs associated with finding a parking space would make the car a more attractive option.

The remaining suite of variables selected for inclusion in both the selector and the outcome equations measures the individual and household-level attributes that are hypothesized to influence the allocation of travel expenditures in maximizing utility. Variable definitions and descriptive statistics are presented in Table 2. As with the variable minutes, four of these—employed, age, numkids, and caravail—are interacted with a female dummy variable to allow differential effects by gender. These variables are of particular interest, as they are indicative not only of the life-cycle stages over which mobility behavior is expected to fluctuate but also of the major sociodemographic changes currently under way in Germany that could dramatically affect future automobile dependency. Between 2000 and 2005, for example, the birth rate decreased some 9.3%, from 9.18 to 8.33 births per 1,000 population, having already decreased 19.5% over the preceding decade (*20*). This trend has been paralleled by an increasingly older age structure of the German population, as well as by an increase in the rates of participation of women in the pool of drivers and in the labor force, with the latter rising from 55.1% in 1994 to 59.2% in 2004 (*21*). Although several studies have suggested that these changes will have profound consequences for transport demand in Germany (*22–24*), the anticipated impacts are largely speculative, and few attempts have been made to quantify how the underlying variables affect travel behavior at the individual level.

With the exception of the identifying variables and the variable measuring automobile availability per licensed driver, which is hypothesized to have a positive coefficient, the variables in Table 2 could either positively or negatively affect automobile use for nonwork activities, and it is not possible to state a priori which effects are expected to prevail. Employed status, for example, would limit the time budget available for nonwork travel while simultaneously increasing the opportunity cost of that time. The former effect would reduce nonwork automobile travel, whereas the latter effect would increase it, given that trips with the automobile generally require less time than trips by other modes. Similarly, an increased distance to work, as measured by the variable commutedist, would decrease the time available for nonwork travel. However, it would also decrease the time for in-home activities, thereby potentially increasing the individual's reliance on market goods and services, such as day care, to substitute for household responsibilities. To the extent that these goods and services are geographically dispersed, nonwork automobile travel could increase with longer commutes (*25, 26*). As similar ambiguities

TABLE 2 Variable Definitions and Descriptive Statistics

Variable	Definition	Mean	SD
Female	1 if respondent is female, 0 otherwise	0.480	0.500
Employed	1 if respondent is employed, 0 otherwise	0.573	0.495
Age	Age of respondent	47.531	15.175
Numkids	Number of children under 18 in the household	0.553	0.894
Commutedist	Kilometers between respondent's residence and workplace	14.097	25.659
Downtown	1 if residence located in a densely settled region, 0 otherwise	0.323	0.468
Caravail	1 if the number of cars in household is greater than or equal to the number of drivers, 0 otherwise	0.565	0.496
Degree	1 if respondent has a college preparatory degree, 0 otherwise	0.340	0.474
Numemplyd	Number of employed persons in the household	1.165	0.884
Minutes	Walking minutes from residence to the nearest public transit stop	5.580	4.685
Prvtpark	1 if private parking space available at residence, 0 otherwise	0.858	0.349
Railtransit	1 if the nearest public transit stop is serviced by rail, 0 otherwise	0.109	0.312

apply to the variables measuring the number of children, the number of employed residents in the household, the age and educational attainment of the respondent, and the indicator for residence in a densely settled area, the sign of the estimated coefficients is left to the empirics. Finally, note that year dummy variables are also included in the model to control for autonomous shifts in macroeconomic conditions that could affect the sample as a whole.

RESULTS

Table 3 catalogues the results from the selector and outcome equations of the Heckman model of car use. Columns one and three contain the coefficient estimates, whereas columns two and four contain the associated transformed marginal effects. In discussing the results, the focus is on the latter effects because they are readily interpreted.

As regards the role of gender, joint tests of the female dummy variables and associated interaction terms in the selection and outcome equations suggests that this variable is statistically significant in determining automobile use ($p < .001$). Nevertheless, unambiguous conclusions as to the sign of gender are not in evidence. Specifically, employment status, age, the number of children in the household, automobile availability, and the proximity to public transit all emerge as intervening factors that complicate the appraisal of gender effects, particularly as regards the discrete decision to use the car.

Employment status has a negative impact on the probability of car use and on the distance driven, with employed people driving roughly 1.56 km/day less than their nonemployed counterparts. The magnitude of the variable's impact is significantly lower for females in the selector equation, although no significant effects by gender are seen in the outcome equation. Relative to unemployed men, the base case of the model, employed women have a lower probability (by .073) of using the car for nonwork travel and a .07 higher probability than employed men. Overall, employed men are the least likely to use the car for nonwork travel, whereas unemployed men are the most likely.

Age, which is specified as a quadratic to capture nonlinearities, is another variable that has differential effects for men and women in the selector equation, although the variable and the interaction terms are insignificant in the outcome equation. The coefficients for age and its square suggest that increases in this variable initially increase but subsequently decrease the probability of nonwork travel, with the peak probability occurring at roughly age 55 years for men and 42 years for women. Further insight into gender differences can be gleaned from Figure 1, which shows the simulated probabilities of car use and confidence intervals obtained by the Monte Carlo technique of King et al. (*13*). The simulations are generated over a range of ages for men and women, whereas the other variables in the model are held fixed at their mean values. Up to the age of 35 years, women have a higher predicted probability than men of nonwork car travel, with a reversal thereafter. Statistically significant differences between the two sexes are, however, indiscernible among cohorts younger than age 45 years, as indicated by the overlap of the 95% confidence intervals.

The coefficient estimate of the variable measuring the number of children has opposite signs in the selector and outcome equations, increasing the probability of nonwork automobile travel but decreasing the distance driven. The latter result, which does not vary significantly by gender, suggests that each additional child reduces the distance driven for nonwork travel by roughly 0.48 km. This is consistent with the idea that children encourage the spending of time at home, particularly during the week, when nonworking hours for out-of-home activities are more limited. That children increase the probability of car use is likely a reflection of the pickup and delivery services associated with child care. Moreover, this effect is seen to be stronger for women, as indicated by the positive and significant coefficient on the interaction term. With respect to the simulated probabilities of the model, Figure 2 illustrates that in households with no children, men have a higher probability than women of undertaking nonwork car travel but that a reversal of roles occurs for households with one or more children. Furthermore, these differences are statistically significant across nearly the entire range of values, with the exception of those for one-child households.

TABLE 3 Heckman Models of Nonwork Car Travel

	Selector Equation: Car Use (1,0)		Outcome Equation: Distance Driven	
	Coefficient	*dy/dx*	Coefficient	*dy/dx*
Female	–0.075 (0.442)	–0.029 (0.445)	–2.531 (0.105)	–2.552 (0.102)
Employed	–0.371 (0.000)	–0.143 (0.000)	–1.484 (0.028)	–1.559 (0.021)
Female*employed	0.259 (0.000)	0.099 (0.000)	0.669 (0.338)	0.668 (0.338)
Age	0.042 (0.000)	0.016 (0.000)	–0.036 (0.634)	–0.014 (0.857)
Agesq	–0.0004 (0.000)	–0.0003 (0.000)	–0.0001 (0.990)	–0.0002 (0.797)
Female*age	–0.010 (0.000)	–0.004 (0.000)	–0.004 (0.876)	–0.009 (0.719)
Numkids	0.070 (0.000)	0.027 (0.000)	–0.521 (0.039)	–0.484 (0.055)
Female*numkids	0.219 (0.000)	0.080 (0.000)	0.251 (0.444)	0.365 (0.261)
Commutedist	–0.002 (0.000)	–0.001 (0.000)	0.031 (0.000)	0.030 (0.000)
Downtown	0.053 (0.019)	0.020 (0.019)	–0.762 (0.010)	–0.753 (0.011)
Caravail	0.149 (0.000)	0.057 (0.000)	0.670 (0.113)	0.767 (0.071)
Female*caravail	0.364 (0.000)	0.142 (0.000)	1.063 (0.055)	1.160 (0.036)
Degree	–0.002 (0.931)	–0.001 (0.932)	0.967 (0.002)	0.967 (0.002)
Numemplyd	–0.012 (0.504)	–0.004 (0.509)	–0.009 (0.971)	–0.015 (0.951)
Minutes	0.006 (0.040)	0.002 (0.039)		
Female*minutes	0.011 (0.012)	0.004 (0.013)		
Prvtpark	0.114 (0.000)	0.043 (0.000)		
Railtransit	–0.131 (0.000)	–0.049 (0.000)		
Selectivity			–0.759 (0.000)	
Constant	–1.317 (0.000)		14.687 (0.000)	
Wald chi2 (18, 13)		126.39 (0.000)		
N_total		44,842		
N_censored		27,044		
N_uncensored		17,798		

p-values in parentheses; year dummies not presented.

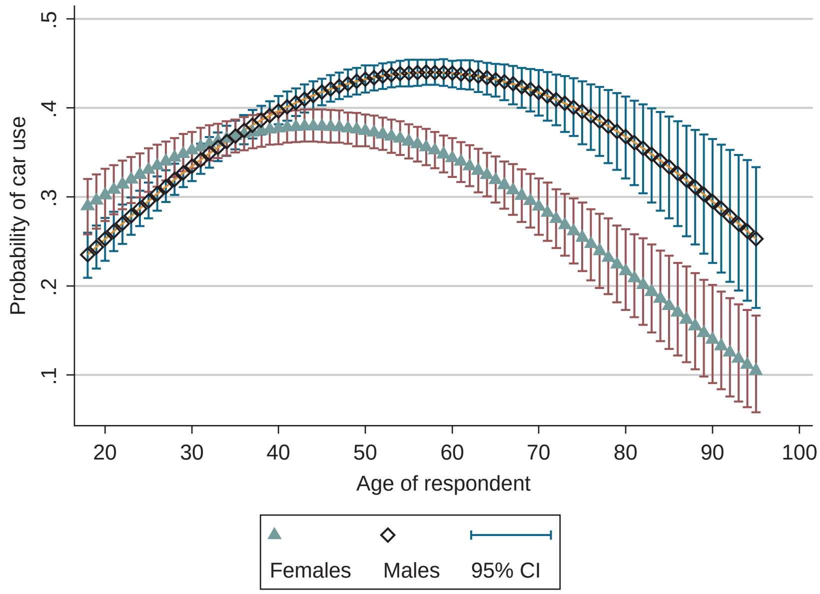

FIGURE 1 Simulated probabilities of car use by age (CI = confidence interval).

As expected, the dummy variable indicating car availability has a positive effect on both the discrete and continuous outcomes. Interestingly, these effects are in both cases significantly higher in magnitude for women. This result is revealing, as it suggests that relaxing the constraint of car availability has an equalizing effect on car usage between the two genders. For example, the model suggests that when households in which the number of cars is equal to or greater than the number of drivers, which comprise just over half the sample, are considered, women have a .11 higher probability than men of using the car for nonwork activities. Although women in such households drive less than men, by roughly 1.39 km, they drive 1.93 km more than women in households in which the number of cars is less than the number of drivers. One possible explanation for these findings is what Pickup (*25*) has referred to as patriarchal constraints—or traditional gender roles—that otherwise limit women's access to the car in cases in which a choice between drivers must be made.

The identifying variable measuring walking time to the nearest public transit has a positive and significant effect on the probability of using the car for nonwork travel, another expected result. The coefficient on the interaction term is also positive and highly significant, suggesting that women respond more strongly to the proximity of public transit than men. The plots in Figure 3 confirm the steeper slope of the effect for women but also reveal the rapidly increasing imprecision of the predicted values. The 95% confidence intervals of the curves increase substantially with time and overlap as of 8 min.

The other two identifying variables both have the expected signs and are statistically significant at the 5% level. The availability of a private parking space increases the probability of nonwork automobile travel

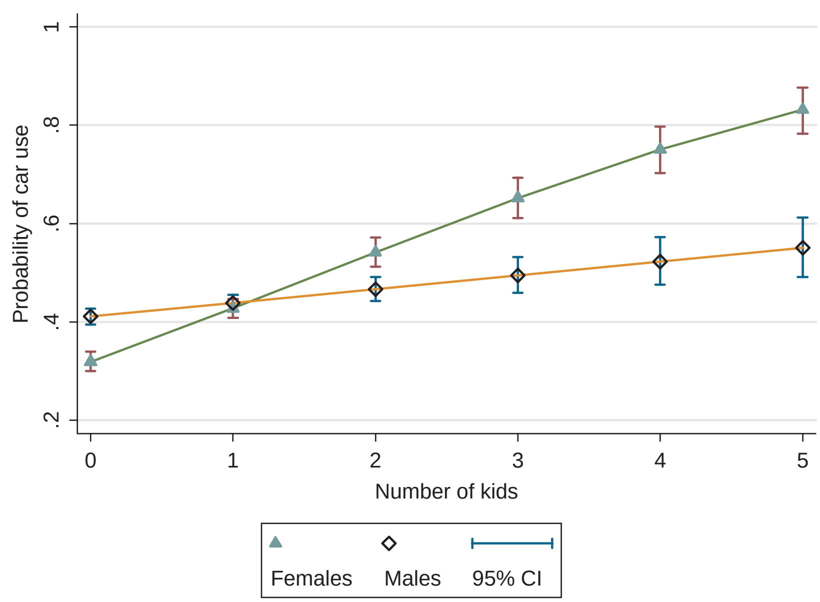

FIGURE 2 Simulated probabilities of car use by number of children.

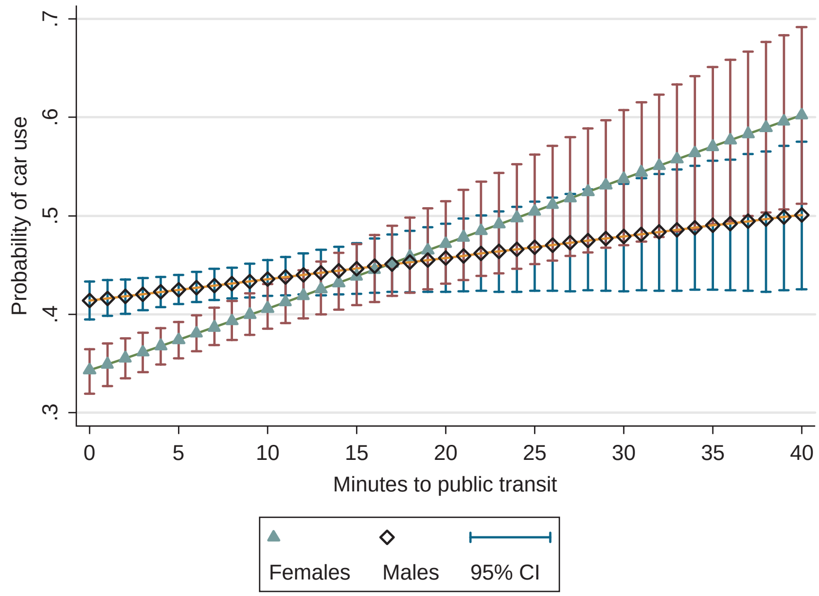

FIGURE 3 Simulated probabilities of car use by walking minutes to public transit.

by .043. If the nearest public transit stop is serviced by rail as opposed to bus, the probability is reduced by .049. Some caution in the interpretation of these and the other neighborhood variables is warranted, given the potential for endogeneity. To the extent that households settle in neighborhoods on the basis of their preferences for the travel amenities offered, the coefficients on these variables could be biased.

Turning to the remaining statistically significant coefficients in the selector equation, individuals with longer commutes have a lower probability of undertaking nonwork travel, whereas individuals residing in a densely settled area have a higher probability. The former result is consistent with the idea that a longer commute would reduce the time available for discretionary activities, whereas the positive effect of residence in an urban environment may reflect the greater array of service and shopping opportunities that would encourage trips by all modes. Interestingly, the signs of the coefficients on these same two variables are reversed in the outcome equation: residence in a densely settled area decreases the distance traveled for nonwork purposes, whereas commute length increases it. Education also has a positive effect. The former findings are likely a reflection of an increased reliance on out-of-home services as functions of commute length and education. That individuals living in an urban environment travel shorter distances corroborates the intuition that higher densities reduce travel demand, although, again, this result may be subject to endogeneity bias because of the simultaneity of residential choice and travel decisions. Finally, the selectivity parameter also is statistically significant, supporting the use of the Heckman model with these data. The coefficient itself is negative, suggesting that, on net, unobservable factors that increase the likelihood of nonwork travel with the car decrease the distance driven.

CONCLUSIONS AND FUTURE RESEARCH

With a focus on individuals in car-owning households in Germany, this analysis has investigated the determinants of automobile travel for nonwork activities against the backdrop of two questions: (*a*) Does gender play a role in determining the probability of car use and the distance driven? and (*b*) If so, how is this role mitigated or exacerbated by other socioeconomic attributes of the individual and the household in which he or she resides? These questions were pursued through a combination of descriptive analyses and econometric methods, the latter of which relied on the Heckman model to control for the effects of sample selectivity.

The descriptive statistics presented at the outset of the analysis suggested that although women, on average, undertake more nonwork travel than men, they undertake less such travel by car, implying a greater reliance on other modes. Nevertheless, the subsequent econometric modeling indicated that it is important to qualify the conclusions drawn with respect to the effect of gender, given the range of confounding factors that mediate its impact. Specifically, it was found that the variables measuring employment, age, the presence of children, the proximity to public transit, and car availability all have significantly different slope coefficients on the probability of nonwork car travel between men and women, with the last variable additionally accounting for differences in the distance traveled.

With respect to gender roles and their implications for mobility behavior, the presence of children, in particular, emerges as an important factor in increasing the probability of car use among women, as evidenced by both the positive coefficient on the interaction term and the simulated predictions from the model. This finding is a likely reflection of the responsibilities associated with child care that are typically borne by women. Car availability also is seen to be an important determinant of nonwork travel by car, having differential effects by gender in both the selector and the outcome equations. Although this effect is positive for both sexes, its magnitude is significantly stronger for women. Viewed alternatively, the result implies that having fewer cars than drivers available in the household disproportionately reduces female car use. Although data constraints limited the ability to explore the role of household power structures, this finding is consistent with Pickup's observation (*25*) that "the general pattern is for husbands to have first choice of car-use." The prevalence of such a pattern also would explain the result that women are more responsive to the proximity of the nearest transit stop. Taken together, these findings support the proposition that women stand to benefit more from policies that improve access to and coverage of the public transit system.

As to the question of whether differences in car use between men and women constitute an important metric for travel demand forecasting, the evidence presented here is mixed. Although the outcome equation revealed few significant differences in the effects of the explanatory variables on the distance traveled between men and women, the significant coefficients on all the interaction terms in the selector equation suggest that the consideration of gender differences in transportation demand analyses may be warranted. Failure to do so could yield inaccurate forecasts, particularly when the significant differences by gender that are revealed by the simulation of predicted probabilities over different age cohorts are considered. Some sense of the magnitude of the discrepancy from neglecting gender differences can be illustrated with a simple back-of-the-envelope calculation of daily nonwork car travel for the demographic segment aged 60 to 64 years, one of the fastest-growing cohorts in Germany. Drawing on population figures from the International Programs Center of the Bureau of the Census (*27*) and multiplying these by the driver's license-holding rate of individuals between the ages of 60 and 64 years (roughly 93% for men and 72% for women) yields an estimated 2.54 million male and 2.53 million female licensed drivers in 2005. If these figures are then multiplied by the predicted values of the distance traveled obtained for each gender from the econometric model and summed, an estimated total of 18.9×10^6 km of daily nonwork car travel for this age cohort is obtained. To compare this figure with one generated in ignorance of gender differences, the model was reestimated, but with the exclusion of the interaction terms (not presented), thereby constraining the gender-specific effects to 0. The corresponding calculation of daily nonwork vehicle travel for the cohort aged 60 to 64 years is 19.9×10^6 km, for a difference of roughly 1×10^6 km, or roughly 5%. Thus, abstracting from the question of distributional effects, this discrepancy points to some—albeit limited—scope for biased aggregate predictions when gender differences are neglected.

Among the important considerations not yet reflected in this analysis concerns the role of trip chaining. A partial explanation for the results may be that men are more successful at trip chaining, increasing the amount of travel undertaken during a given trip (or a given day when the amount of time for nonwork travel precludes more than one trip per day). Other considerations include the jointness of nonwork trip decisions and larger life decisions: underlying the differences between the sexes with respect to nonwork travel may be differences in where adult men and women live and work, as well as what they do for a living. One promising approach to pursuing these issues further would involve augmentation of the data set used here with measures of urban form, such as access to a highway as well as road and building densities, ideally accounting for the potential endogeneity of these variables to disentangle correlation from causation.

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